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Examining the process of normalising the energy-efficiency targets for coal-based thermal power sector in India

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ABSTRACT

Setting targets and normalising them are two of the most important elements in the recently introduced market-based climate-change mitigation policy—Perform, Achieve, and Trade (PAT)—in India. The scheme permits, in the monitoring and verification phase, normalisation of the efficiency realisation against unfavourable working conditions. On the one hand, such normalisation brings the energy efficiencies of plants operating in different conditions to a common level, on the other hand, adjustments resulting from normalisation are likely to provide free-riding benefits, and in addition, results in alteration of efficiency realisation. This may be a source of distortion in the market expectation, resulting in trading phase uncertainties. This paper examines the effects of normalisation on the specific energy consumption in the context of the PAT scheme in the coal-based power sector. The paper makes a cross-sectional analysis involving data envelopment analysis and Tobit regression. The results indicate that effect of variation in system demand, planned maintenance time, forced outage, fuel quality, and fuel mix on specific energy consumption is substantial. However, the effect of the variability in coal quality and fuel mix is significantly higher than the other variables. Therefore, use of clean-coal is suggested to stabilise the specific energy consumption for a stable certificate market.

1. Introduction

Energy efficiency improvement is globally accepted as an approach to sustainable energy supply and emission reduction. In this context, market-based energy efficiency policies have gained popularity across many countries. India has recently introduced, under its climate-change mitigation policy, a market-based scheme—Perform, Achieve, and Trade (PAT)—to achieve energy efficiency in various sectors. As part of this scheme, a unit-wise reduction in specific energy consumption is envisaged by specifying plant-specific targets [4,7,24].

In order to take into account the effect of intra-sector diversity in operating conditions, the set targets are normalised with an objective of measuring energy efficiency in a level playing field. The most tricky part of this exercise is the ex ante determination of the explaining variables of the working conditions that are beyond the control of the plant management, since the outcome of the energy efficiency scheme can be greatly influenced by the normalisation mechanism [15,5]. In the present study, we examine, in the context of India's thermal power plants, whether the uncontrollable variables forming the criteria for normalisation have any influence on the plant performance, and, if so, to what extent such uncontrollable variables influence the energy efficiency of the plants.

Normalisation or correction of targets, ex-post, is a widely accepted feature in the market-based energy efficiency schemes. It is applied to ensure that a plant is not penalised for a condition, which is beyond its control [16,19,25]. It is possible that this facility may be misused by the plants. Since the process of normalisation offers an opportunity for adjustment of the targets, it is likely that the obligated plants may attribute the cause of the plants' non-conformance to the adverse working conditions, and seek correction in the targets within the normalisation framework. Furthermore, adjustment of efficiency realisation at a later stage is likely to distort the expected certificate entitlement, and therefore, may result in uncertain trading phase [17,6].

To guard against such a possibility, it is important that the variables forming the basis of normalisation should be uncontrollable (i.e., not influenced by managerial decisions) and should directly or indirectly influence a plant's energy efficiency. Considering the important role played by the market-based energy efficiency policies in ensuring energy security and emission reduction, we set our objective to examine the effect of normalising factors on the effectiveness of the PAT scheme.

In this context, we focus on two key issues associated with the process of normalisation in the PAT scheme in India:

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Table 1
Factors used in different studies for performance analysis.

Authors	Variables used for determining performance
Singh [30]	Capacity and Unit size
Sinha [31]	Plant design, Vintage, Plant location, Major equipment manufacturer and Operational pattern
Khanna and Zilberman [20]	Coal quality
Shukla et al. [28,29]	Fuel character, Choice of technology, Size, Vintage, Ownership pattern, Management pattern and Maintenance schedule.
Shanmugam and Kulshrestha [27]	Capital, Coal consumption, Oil consumption and Auxiliary power consumption
Sanpasertparnich and Aroonwilas [26]	Coal quality, Steam cycle efficiency
Yang and Pollitt [35]	Fuel quality, scale of operation
Yu et al. [36]	Weather condition
Bajpai and Singh [2]	Coal and oil consumption, Auxiliary power consumption, Installed capacity and Operational time

(1) Do the normalising factors of the PAT normalisation mechanism have any significant influence over energy efficiencies of Indian coal-based thermal power plants?
(2) To what extent each of these factors influences the efficiency of coal-based thermal power plants?

We have examined energy efficiency and environmental performance of 69 coal-based thermal power plants in India, which are obligated under the PAT scheme to improve energy efficiency. Data Envelopment Analysis (DEA) and Tobit regression are applied to examine the effect of uncontrollable variables used for normalisation on the plant performance. The outcome of the study indicates that:

1. Five of the six normalising variables have a significant influence on the energy efficiency of the plants, the coal quality, grid operating conditions and the fuel mix being the most dominant.
2. The fuel supply reliability does not have any significant influence on the energy efficiency.

While the first result implies that normalising the efficiency targets is rational in the context of variability in operating conditions in India. The second result, however, clearly points to a possibility that under the present normalisation criteria of the PAT scheme, an inefficient plant may get its heat rate adjusted against fuel supply constraint and earn certificates—a free riding benefit—even though the fuel supply has very little impact on heat rate.

The remainder of this paper unfolds as follows: Section 2 makes a survey of literature on normalisation in energy efficiency certificate schemes, variables affecting the specific energy consumption, and on the application of DEA in estimating the effect of the uncontrollable variable. Section 3 presents the theoretical background, target setting, and normalisation mechanism, and the research questions raised. Section 4 formulates the DEA model, describes the Tobit regression model for estimating the effect of uncontrollable normalisation variable. The ways of selecting and collecting data for applying them to the models are presented in Section 5. Section 6 analyzes the results obtained from the models in the case of the coal-based thermal power sector in India, and Section 7 concludes the paper and indicates the scope of future work in this area.

2. Literature review

2.1. Normalisation and energy efficiency schemes

Normalising the targets for any temporal and spatial diversity of variables affecting efficiency is a common feature in market-based energy efficiency schemes [25]. For example, in Italian energy efficiency scheme, the baseline energy savings stipulated on the basis of technical evaluation is adjusted using a default factor. Similarly, in the UK, the baseline efficiency is standardized considering the technology used and fuel type [16]. However, normalisation or standardization of efficiency realisation during monitoring and verification phase alters the market expectations because the adjustments made through normalisation distorts the outcome of the tradable efficiency scheme [17,6]. Therefore, for a credible energy efficiency scheme and predictable certificate market, the normalisation mechanism should be designed in such a manner that normalisation should not result in substantial alteration of expected efficiency realisation.

In the PAT scheme of India, the target is normalised in the assessment year on the basis of a set of criteria specifying the operating conditions and fuel quality [5,7]. The scheme recognizes five normalisation factors [15,5]. They are the quality of fuel, fuel mix, fuel availability, breakdown, and unscheduled outage. In order to justify the selection of the normalisation factors, it is crucial to understand the causal relation between these factors and the plant performance. A number of studies reported in the past have each identified different sets of factors that influence the energy efficiency of thermal power plants. Table 1 gives the set of factors identified by these studies

These studies, no doubt, have made a significant contribution to the specific area of power plant performance, but there has not been any study that divides the influencing factors into two sets of controllable and uncontrollable factors and separately finds their effect on plant performance.

Regression analysis [30,31], simulation study [22,26], and DEA [2] are the most popular methodologies applied to examine the effect of different variables on the performance. However, DEA combined with censored regression is widely applied to examine the effect of uncontrollable variables on the efficiency [12,18,35,36].

While the studies by Yang and Pollitt [35] focused on power plant performance, Yu et al. [36] examined the effect of weather conditions on the performance efficiency of electrical transmission and distribution systems in the UK. The studies by Hu et al. [18] examined the effect of external environment on the regional energy efficiency of 23 regions in Taiwan and Fang et al. [12] examined how the energy efficiency and energy saving targets are affected by the characteristics of different service sectors.

The common feature of the above-stated studies is that they applied DEA for efficiency analysis and regression method for examining the effect of the uncontrollable variables. This combined method has been found to provide reliable insights, since it leverages the strength of DEA in handling multiple inputs and outputs, and the robustness of regression method in establishing the relation of (in)efficiencies with the uncontrollable variables [10,35]. The present study has used this combination approach of DEA and regression analysis to examine the effect of normalisation variables on plant performance.

2.2. Efficiency estimation and uncontrollable variable using DEA

Charnes et al. [9] was the first to propose DEA as a non-parametric method of performance analysis. Its application in the performance study of the power sector has been extensive [38].

To incorporate the effect of uncontrollable variables on performance, four variations in the basic DEA model have been proposed. They are the one-, two-, three- and four-stage models. In the one-stage

Table 2
Target setting criteria for thermal power plants under the PAT scheme.

Deviation in Net Heat Rate from design Net Heat Rate	Reduction target for % deviation in the Net Heat Rate	% reduction target in Net Heat Rate
Up to 5%	10%	0.5
More than 5% and up to 10%	17%	0.85–1.7
More than 10% and up to 20%	21%	2.1–4.2
More than 20%	24%	4.8 and above

model, the uncontrollable variables are incorporated within the DEA formulation, but they are specified as fixed or semi-fixed [3]. But by restricting the uncontrollable variables, efficiency measurement is done with reference to a unit with similar conditions of the uncontrollable variable. Therefore, even though the model by Banker and Morey [3] has been widely used for its simplicity, it requires a prior decision regarding the direction of influence of the uncontrolled variable. Secondly, with increasing number of uncontrollable variables, the number of efficient units increases, thereby diminishing its discriminating power [10,13,35].

The two-stage model, proposed by Fried et al. [14], starts with a conventional DEA analysis, and in the second stage, the efficiency score is regressed against the uncontrollable variables. The second stage analysis involves the application of censored regression methods such as Tobit or logistic regression of the DEA efficiency score against the uncontrollable variables. Yu et al. [36] used a two-stage model to determine the effect of weather on the cost and quality performance of UK electricity distribution company. Zhang et al. [37] examined the effect of various market-based climate-change policy-tools on the efficiencies of Swedish industries, applying the two-stage model, and Wu et al. [33] determined the influence of environmental factors on productive efficiencies of wind farms in China following the same model. Although this approach addresses the shortcomings of the one-stage model, it does not utilise the information contained in the slack or surplus variables and therefore has limited ability to estimate the cause of the inefficiency [10].

A three-stage model proposed by Fried et al. [14] uses the information contained in the slacks to estimate the cause of the inefficiency. The first stage of the three-stage model is same as the first stage of the two-stage model, but in the next stage, the DEA slack is regressed against the uncontrollable variables. In the third stage, the stochastic frontier analysis is used, and the total slack is decomposed into the impact of uncontrollable variables, management inefficiency, and statistical noise. For example, Yang and Pollitt [35] examined, in addition to desirable and undesirable outputs, the effect of uncontrollable variables by applying the three-stage model. Xie et al. [34] estimated the environmental efficiency and marginal abatement cost of carbon di-oxide under the influence various environmental factors, and Li and Lin [21] determined the effect of Government measures on green productivity growth in China, using the three-stage DEA model.

The shortcomings of the two-stage model are also addressed in the four-stage model proposed by Fried et al. [13]. In this model, the slacks are regressed with the uncontrollable variables to indicate the impact of the uncontrollable variables on the slacks. The input data are then adjusted with reference to the impact of the uncontrollable variables and used for the final stage. In this method, the efficiency score of each unit is adjusted with the average efficiency [13,14].

These models vary in terms of computational simplicity and accuracy of results. In some cases, the one-stage and the two-stage models are preferred due to their simplicity in the application [36], but the three-stage and four-stage models are considered superior both in terms of their accuracy and utility [10,35].

In the recent times, the four-stage model is witnessing a wide variety of applications. For example Hu et al. [18] applied the four-stage model to estimate the regional energy efficiency incorporating the environmental conditions. And, Fang et al. [12] derived the energy efficiency of the service sector by incorporating the environmental conditions.

3. Theoretical background and research questions

3.1. Criteria for target setting in thermal power plants under the PAT scheme

According to the PAT scheme, a target is set for the heat rate reduction of each plant, and it is to be realised within a specified period. At the end of that period, the plant is either penalised or awarded with energy efficiency certificates depending upon the level of compliance [4,7]. The target for the heat rate reduction for a plant is determined as a fraction of deviation of the base-year heat rate from the design heat rate, with a step-rise in the fraction as the deviation increases. The target-setting criteria adopted in the PAT scheme for the thermal power sector are presented in Table 2.

In case a plant is subjected to unfavourable working conditions, such as poor quality of coal, irregular coal supply, variable load conditions and plant shut-down due to unforeseen situations etc., the heat rate is normalised against such unfavourable working conditions so that it is not penalised due to the factors that are beyond its control.

In the process of normalisation, the gain in the heat rate is determined due to unfavourable conditions, such as poor coal quality, plant load factor, outage, plant availability, and auxiliary power consumption by pollution control equipment, and is deducted from net heat rate of the plant determined in the assessment year [5]. The number of certificates to be earned (bought) are then determined on the basis of the heat rate in the assessment year after normalisation [15,5]. The factors used for normalisation under the PAT scheme for the thermal power sector, corresponding explaining variables and the method of evaluation are explained in Table 3 [5].

3.2. Research questions

The justification for the selection of normalisation variables rests on two implicit assumptions: (1) The variability in the factors shown in Table 3 have the potential to significantly alter the energy efficiency, and (2) The variables representing these factors are uncontrollable from the managers' perspective. In this paper we examine the causal relation between the uncontrollable variables and the performance, and formulate our research questions as the following:

Table 3
Variables used for normalisation of power plant heat rate under the PAT scheme.

Factors	Explaining variables	Latent variables	Method of normalisation
Coal quality	Gross calorific value of coal (GCV)	Boiler efficiency	Empirical equations
Fuel Mix (Secondary fuel)	Specific secondary fuel consumption (SFC)	Boiler efficiency	Direct measurement
Fuel availability	Fuel supply reliability (FSR)	Load Factor	Characteristic curves
Breakdown	Planned maintenance (PM)	Load Factor	Characteristic curves
Unscheduled outage	Partial unavailability due to low system demand (LSD), and forced outage (FO)	Load Factor	Characteristic curves

a) Does the-the intra-sector variation in variables representing uncontrollable operating conditions, as per the PAT normalisation criteria, significantly influence the energy efficiency of thermal power sector?
b) What is the relative strength of each of the variables in influencing the specific energy consumption in the context of PAT normalisation mechanism, and how can the effect of normalisation be minimised, so that a stable market for energy efficiency certificate is realised.

4. Methodology

The research questions in the foregoing section require the estimation of the effect of the uncontrollable variables on plant efficiency. To answer these questions, this paper has followed two steps. In the first step, a plant-wise efficiency is determined using a four-stage DEA model, and, in the second step, the results of plant-wise DEA efficiency score without considering the effect of normalisation variables, and DEA score adjusted with the effect of normalisation variables are compared using Kruskal-Wallis Rank-Sum test.

4.1. Four-stage DEA process

4.1.1. DEA formulation

A DEA model is formulated representing a technology structure in alignment with the PAT objective. Assuming that we have N decision-making units (DMUs) using P inputs to produce Q outputs, the input matrix is defined as $X \in R_+^{N\times P}$, and $Y \in R_+^{N\times Q}$ is defined as the output matrix. The minimum heat rate is achieved when electricity is generated with minimum amounts of inputs. Therefore, the DEA is formulated with the objective of determining the relative efficiency of electricity generation at the minimum level of inputs, so that the heat rate—a ratio of input energy with electricity generated—is minimised. The technology structure is therefore represented by an input-oriented radial model under the assumption of constant returns to scale and is formulated as follows:

$Min\theta$

subject to

$$X\lambda \le \theta x_o, \quad (1)$$

$$Y\lambda \ge y_o, \quad (2)$$

$$\lambda \ge 0, \quad (3)$$

$For\ j = 1,\ldots,N$

Here λ represents the intensity vector of the DMUs. The subscript o represents the oth DMU whose efficiency is being determined. Capacity, Plant Load Factor (PLF), coal consumption, and auxiliary power consumption are used as the inputs and electricity generation is used as the output.

4.1.2. Tobit regression

Tobit regression is a special case of censored regression model which establishes the relationship between the explanatory variables (X) and the dependent variables (Y), where the dependent variable is either censored from above or below (right or left), $\beta$is the vector of regression coefficients, and ϵ is the error term assumed to be normally distributed, $\epsilon \sim (0,\sigma^2)$. For M uncontrollable variables the Tobit model can be expressed as:

$$Y^* = \beta_0 + \sum_{m=1}^{M} \beta_m \bullet X_m + \varepsilon \quad (4)$$

$$Y = Y^*, for\ Y^* > 0 \quad (5)$$

$$Y = 0, \quad for\ Y^* \le 0 \quad (6)$$

Following Fried et al. [13], the total slack—sum of the radial and the non-radial slacks obtained from the DEA analysis—is treated as the dependent variable, which is regressed with the normalisation variables that are considered as the independent variables. Zero input slack implies a fully efficient DMU in an input-oriented formulation, and thus the minimum expected value of total slack for any DMU is more than or equal to zero. Therefore, a left-censored slack value is regressed against the normalisation variables. The regression coefficients are then used to adjust the input variables, which reflects the effect of normalisation variable on the plant efficiency.

4.1.3. Adjustment of input variables and efficiency

Considering that the DEA is formulated with P inputs, there are P slacks (dependent variables), and each slack is expressed as a function of normalisation variables (Z), Tobit regression coefficients (β), and the error terms (ε):

$$s_j^p = f^p(Z_j;\beta^p;\varepsilon^p) \ \ for\ p = 1 \ldots P \quad (7)$$

where,

Z_j is the vector of normalisation variables corresponding to the jth DMU;
β^p is the vector of regression parameters corresponding to the pth input against the normalisation variables; and,
ε^p is the statistical noise corresponding to the pth variable.

Following Fried et al. [13], Yang and Pollitt [35], Hu et al. [18], and Fang et al. [12], the inputs are adjusted for the worst operating condition across the thermal power sector:

$$x_p' = x_p + (Max\{f^p(Z_j;\beta^p)\} - f^p(Z_j;\beta^p)) \ \ for\ p = 1 \ldots P \quad (8)$$

The dependent variable s_j^p in Eq. (8) is the total slack (sum of radial and non-radial slacks), and the normalisation variables Z_j are the independent variables corresponding to the plant j. Therefore, Tobit regression establishes the relation between the excess inputs and the normalisation variables, and the function $f^p(Z_j;\beta^p;\varepsilon^p)$ can be used to predict the slack s_j^p for plant j corresponding to input p operating in a condition defined by Z_j. It is however rational to presume that the maximum value of $f^p(Z_j;\beta^p;\varepsilon^p)$ corresponds to the maximum slack, which indicates that the plant operates in the least favourable condition. Therefore, in order to eliminate the effect of Z_j for the plant j, the input is adjusted by adding, the deviation of slack of the plant with reference to the plant that is operating in the least favourable condition. The second term to the right of Eq. (8) represents the excess input that would be consumed, if it operates in the least favourable condition. Therefore, the term x_p' in Eq. (8) represents the pth input of plant j, if it operates in the least favourable condition.

In the fourth stage, the DEA efficiency is determined by using the adjusted value of inputs applying the formulation in Eq. (1). The unit-wise efficiency scores with pre-adjusted input and post-adjusted inputs are compared to examine whether they are significantly different.

5. Application in the case of thermal power sector

5.1. Selecting the variables

Conventionally, controllable factors, capacity, coal consumption, auxiliary power consumption, and plant load factor, are chosen as the input variables, and electricity generation is chosen as the output for a thermal plant efficiency analysis. In addition, our study considers the variables representing the normalisation factors in the PAT scheme for the thermal power plants are chosen as the uncontrollable variables [5]. The list of controllable and uncontrollable input variables and the output variables used in the study are summarised in Table 4.

Table 4
Input, output and uncontrollable variables.

Output variables	Input variables	
	Controllable	Uncontrollable (normalisation)
Electricity generation (GEN)	Capacity (CAP) Coal consumption (CC) Auxiliary power consumption (APC) Plant load factor (PLF)	Low system demand (LSD) Forced outage (FO) Planned maintenance (PM) Fuel supply reliability (FSR) Gross calorific value (GCV) Specific secondary fuel consumption (SFC)

5.2. Description of normalisation variables

i. *Unscheduled outage*: Electricity is supplied instantly in the quantity demanded. There is no provision of inventorying electricity. During operation, a plant encounters variable demand and supply conditions. Therefore, a power plant must be in readiness to generate power as and when the demand arises. A reserve shutdown (*RSD*) condition is encountered when the plant operation has to stop due to a lack of demand, and a condition of partial unavailability is encountered when there is excessive variation in system load or there is low system demand (*LSD*). The demand side conditions are described by the loss of generation due to *RSD* or *LSD* [8].

ii. *Planned Maintenance*: A plant remains unavailable for power generation when it is shut down for annual planned maintenance.

iii. *Forced Outage*: A plant is forced to shut down when coal is not available in adequate quantity or there is a breakdown of equipment rendering the plant to stop operation. The forced outage hours and planned maintenance are expressed in terms of percent of generation hours lost out of total available hours [8].

iv. *Fuel Supply Reliability:* Reliable supply of coal is considered as an important variable to ensure uninterrupted plant operation and plant performance [22]. In India, the power plants usually enter into a long-term agreement with the coal companies to supply coal, and the authors determined the deviation of actual supply from the contracted quantity as a measure of fuel supply reliability (FSR) applying the following expression:

$$FSR = 1 - \frac{Q_{ass} - Q_{sup}}{Q_{ass}} \quad (9)$$

Here, Q_{ass} is the contracted quantity of coal supply in a year to and Q_{sup} is the quantity of coal supplied to the plant in the corresponding year. Thus, *FSR* of 1.0 or more indicates an adequate supply for uninterrupted operation and *FSR* of less than 1.0 indicates interrupted supply leading to an occasional shortage.

v. *Primary Fuel Quality*: Coal is used as the primary fuel in coal-based thermal power plants. The quality of fuel is determined by its intrinsic property such as gross calorific value (*GCV*) or higher heating value of the fuel. The *GCV* indicates the thermal energy released when one unit of fuel is burnt.

vi. *Secondary Fuel Consumption*: Secondary fuels are used to supplement the primary fuel for stable boiler operation [1]. Petroleum based fuels such as light diesel oil, fuel oil, high-speed diesel are used as the secondary fuel. Plant-specific volumetric consumption of fuel used per annum expressed in kiloliter is used in this study.

5.3. Data collection

The Central Electricity Authority (CEA) of the Government of India monitors the plant performance parameters such as planned maintenance, forced outage, plant availability and resource inputs like consumption of coal, and use of secondary fuel. The plant performance data on forced outage, unit size, vintage structure, conditions of grid and fuel quality used in the study were collected from the published database maintained by CEA [8].

5.4. Determining efficiency without normalisation

An input-oriented DEA model is formulated following Eq. (1) by considering plant capacity, coal consumption, auxiliary power consumption and plant load factor as the inputs and electricity generation as the single output. Under the PAT scheme, 97 coal-based power plants with a cumulative capacity of 78,860 MW are obligated to reduce their heat rates [4], but, due to constraints of data availability, the present study is conducted using the dataset of 69 plants. Altogether they cover 71.1% of the total coal-based plants and 90.7% of their capacity. All the large plants are covered in this study, therefore, the results of this study can be considered as a fair representation of the thermal power sector obligated under the PAT scheme. The general statistics of the selected model variables for the entire lot of 69 plants are presented in Table 5. The names of the plant, their capacity, ownership and efficiency scores are presented in Appendix A. It may be noted that the plants have been classified as Central-Government-owned, State-owned and Private, based on their ownership.

For the purpose of analysis and subsequent interpretation, the authors have classified the plants as small (Less than 500 MW), medium (500 MW to up to 1000 MW) and large (More than 1000 MW). This classification is also followed by the power plant professionals in an informal manner. Table 6 gives the number and total capacity under each class.

The unit-wise data on normalisation variables for the year 2010 are compiled from the published report of CEA [8] and the general statistics of the normalisation variables are presented in Table 7.

6. Results and discussion

The present study uses DEA to determine unit-wise efficiency scores in India's thermal power sector. Assuming that the inefficiency is caused by adverse conditions of uncontrollable normalisation variables, the input slacks from the DEA analysis are regressed against the uncontrollable variables to estimate the contribution of uncontrollable variables to each inefficient unit. The regression parameters are then used to normalise the inputs against the worst condition of uncontrollable variables, and the inputs, adjusted for the worst condition, are used to determine the efficiency. Therefore, the efficiency score with the adjusted value of inputs represents the efficiency score had the plant operated in the worst condition of uncontrollable variables.

Table 5
Statistics on input-output data.

	Capacity (MW)	Plant Load Factor (%)	Coal consumption ('000 t/year)	Auxiliary power consumption (%)	Generation (million unit)
Max	3260.0	102.33	18,081.00	14.79	27,585.85
Min	62.5	9.62	262.00	4.79	264.71
Average	1027.2	73.27	4653.07	9.48	6532.04
Std. Dvn.	697.6	21.45	3829.62	2.25	5635.48

Table 6
Classification of the power plants.

Category	Capacity range	Numbers	Total capacity MW
Small	< 500 MW	18	5832.5
Medium	≥ 500 MW and < 1000 MW	20	14,895.0
Large	≥ 1000 MW	31	50,842.3
Total		69	71,569.8

Table 7
Statistics of normalisation variables.

	LSD	PM	FO	FSR	GCV
Max	25.830	35.480	65.770	1.447	5486.765
Min	0.000	0.000	0.640	0.569	3076.543
Mean	9.499	6.663	11.232	0.987	4083.364
Std. deviation	8.1426	6.3046	13.8497	0.1545	524.9955

The DEA analysis is done by DEA Solver-pro 2.1, the Tobit regression was conducted by using the statistical software Stata 14, and other computational tasks are accomplished through Microsoft Excel 2010.

6.1. Correlation between the normalisation variables

The correlation coefficients of normalisation variables across 69 thermal power plants for the year 2009–2010 are presented in Table 8. It can be clearly seen that the correlation coefficients between all the variables are relatively low, thus ensuring that the normalisation variables are independent of each other. Low correlation coefficients also ensure that the Tobit regression of input slacks against the normalisation variables are fairly unbiased. Correlation between SFC and log(SFC) is high (0.82), as expected, since log(SFC) is the logarithm of the secondary fuel consumption, and SFC represents the secondary fuel consumption. The correlation coefficients between the remaining uncontrollable variables are less than 0.5, indicating that the uncontrollable variables used for normalising the energy efficiency of thermal power plants are reasonably independent.

6.2. Base model efficiency

The efficiency scores are determined by applying DEA as per the formulation in Eq. (1) and by taking the controllable variables (Refer to Table 4) as the input and electricity generation as the output. The summarised results obtained from the DEA model are presented in Table 9. Three plants in large category and one from the medium category have full efficiency score of 1.0%, and 42% of the plants are within the range of efficiency scores of 0.8% and 0.99% and 52% have an efficiency score of lower than 0.8. The minimum efficiency score is 0.4.

To determine the cause of inefficiency, the total slacks—the sum of radial and non-radial slacks—are determined corresponding to each input variable. The DEA-solver Pro 2.1 reports the non-radial slacks, and the radial slacks are determined from the projection of the input variables on to the efficiency frontier.

Table 9
Performance of plants.

	Efficiency score	Number of plants			Total number of plants
		Small	Medium	Large	
High performer	1.0	0	1	3	4
Moderate performer	0.8–0.99	5	8	16	29
Low performer	< 0.8	13	11	12	36
Total		**18**	**20**	**31**	**69**

6.3. Regression with normalisation variables

The total slacks of each unit, when regressed with the sets of normalisation variables, yield regression coefficients along with their standard errors as summarised in Table 10.

Table 10 shows that, for fuel supply reliability (FSR) and the secondary fuel consumption (SFC), the regression parameter values are not significantly different from zero, even at the significance level of 10%, against any of the input slacks. This implies that the input slacks are not likely to be affected by fuel supply reliability and the secondary fuel consumption. Therefore, in the next step, Tobit regression is repeated by dropping these two variables, and the results are presented in Table 11. The results show that by excluding fuel supply reliability and the secondary fuel consumption, the *p*-value for capacity-slack and the PLF-slack exhibit substantial improvement, and indicates improved significance for regression coefficients.

The results of the regression suggest two important aspects of the normalisation framework of the PAT scheme with respect to the thermal power sector of India. First, the reliability of fuel supply does not seem to affect any of the inputs, thus, this variable may not have any significant effect on the heat rate. This implies that either the fuel supply across the sector is fairly stable or the loss of generation due to short supply of fuel is reflected in another variable. Second, contrary to our expectation, coal consumption was affected more due to the variation in planned maintenance (PM), forced outage (FO), and coal quality represented through gross calorific values (GCV) than due to the variation in fuel supply (FSR).

6.4. Normalisation-adjusted efficiency

The inputs are then adjusted by taking into consideration the normalisation variables as discussed in Section 4.1.3, and the efficiency scores are again calculated with the inputs adjusted with the Tobit parameters corresponding to the normalisation variables. It may be seen that, out of the five normalisation variables retained for analysis (Table 11), three variables, low system demand (LSD), planned maintenance (PM) and forced outage (FO), explain the supply-side variability and the remaining two, gross calorific value (GCV) of coal,

Table 8
Correlation between the normalisation variables.

	LSD	PM	FO	FSR	GCV	SFC	Log SFC
LSD	1						
PM	0.080157	1					
FO	0.427459	0.261856	1				
FSR	− 0.28063	− 0.26674	− 0.29559	1			
GCV	0.100218	0.146967	0.3563	− 0.32825	1		
SFC	0.44881	0.039678	0.102201	− 0.04987	− 0.13805	1	
Log SFC	0.495852	0.133151	0.21799	− 0.10575	− 0.0863	0.823819	1

Table 10
Tobit regression coefficients and their standard errors.

	Cap Slack		PLF Slack		CC Slack		APC Slack	
	Coefficient	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**
LSD	2.235295	4.603391	0.9883932**	0.4480711	10.32458	11.17713	0.3842874***	0.0638435
PM	3.730239	4.948699	− 0.2141338	0.4823039	5.649495	12.02008	0.1697733**	0.0687395
FO	6.619543**	2.559467	− 0.244348	0.2496309	− 11.16726*	6.222645	0.1758654***	0.0355699
FSR	83.74131	213.8309	9.834217	20.72356	451.4479	517.8588	− 1.072637	2.955699
GCV	− 0.1336845**	0.0632068	0.0051667	0.0061123	− 0.8268793***	0.1539672	0.000323	0.0008697
SFC	− 0.002153	0.0053676	0.0008472	0.0005213	0.0056983	0.0130182	0.0000958	0.0000743
Log SFC	189.6738*	112.6626	− 34.46128**	10.85564	344.6973	272.633	− 2.839717*	1.547658
Log likelihood	− 451.38607		− 301.65868		− 510.18742		− 175.05013	
Prob > chi^2	0.0020		0.0450		0.0000		0.0000	

*, **, and *** indicate significance at 10%, 5%, and 1% respectively.

and log of secondary fuel consumption (log(SFC)), are the demand-side variables. In order to examine the effect of these two sets of normalisation variables, the input slacks obtained from the base model are first regressed with the supply-side normalisation variables, and the inputs are adjusted with corresponding Tobit parameters. Similar steps are repeated with the demand-side variables. The regression parameters with respect to the supply-side and demand-side variables are presented in Tables 12, 13 respectively.

The Tobit regression coefficients are observed to be fairly consistent and can be considered as statistically significant. The efficiency scores are adjusted using the Tobit coefficients as explained in Section 4.1.3, and efficiency scores are derived with adjusted inputs using the Eq. (1).

The efficiency scores obtained with the input datasets adjusted with supply-side, demand-side and all the normalisation variables are determined and compared with the base-model score separately, applying the Kruskal-Wallis rank-sum test. The average scores and the H-statistics are presented in Table 14.

The Kruskal-Wallis test examines the difference in the mean of ranks of the population and tests the null hypothesis that the samples are drawn from the same population.

For 1 degree of freedom, at α = 0.05, $\chi^2_{0.05,1}$ = 3.841, therefore the null hypothesis that, the efficiency score of the base model and models with inputs adjusted with both-side normalisation variables have equal means is rejected. This implies that variability in the normalisation variables significantly alters the efficiency scores, thus this result validates the normalisation criteria. On similar arguments, the null hypothesis that the base model and the model adjusted with demand-side inputs have equal means is also rejected at α = 0.05. However, since at α = 0.01, the $\chi^2_{0.01,1}$ = 6.63, the null hypothesis that the samples of DEA model efficiency score and the score adjusted with only supply-side normalisation variables come from the population with equal means cannot be rejected at 1% significance level.

This implies that variability in two demand-side variables, namely, coal quality and in the log-linear function of secondary fuel consumption, alters the energy efficiency at a significance level of 1% . Therefore, the argument that the heat rate (i.e, the specific energy equivalent) for thermal power plants be adjusted against coal quality and secondary fuel consumption is justified. For example, the heat rate of the plants is to be revised downwards for plants that receive poor quality coal relative to other plants. This result also validates the study by Khanna and Zilberman [20] and Mathur et al. [22] that using clean-coal in Indian thermal power plant can significantly reduce greenhouse gas emission realised through efficiency improvement.

6.5. Policy implication

The results obtained from the foregoing analysis points to the fact that, out of six normalisation criteria under the PAT scheme, the heat rate of the power plants are largely influenced by the quality of primary fuel (coal) and secondary fuel consumption. The study also points out that, the fuel supply reliability may be a redundant variable from PAT-normalisation point of view. We, therefore, discuss the implication of normalising the heat rate against these variable on energy efficiency.

Firstly, it is a known fact that frequent disruption in fuel supply may result in frequent shut downs and start-ups affecting the heat rate. However, the results obtained from the present study indicate that the variation in the rate of fuel supply by the coal companies does not have a significant bearing on the heat rate of power plants. This implies that either the fuel supply system to the power plants are consistent, and therefore incidents of disruption in power generation due to a shortage of fuel is not pervasive, or, the frequency of shut-downs and start-ups due to fuel shortage is not significant to affect the heat rate.

Secondly, the secondary fuel is used in a power plant, either to supplement the primary fuel in the case of inconsistency in primary fuel quality, or, to stabilise the boiler operation in the case of low system demand or excessive variation in system demand. In coal-based power plants, the most common form of inconsistency occurs in ash content and moisture content of the coal. However, a low correlation

Table 11
The final Tobit regression coefficients and their standard errors.

	Cap Slack		PLF Slack		CC Slack		APC Slack	
	Coefficient	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**
LSD	1.625277	4.470272	1.046417**	0.4450087	9.023164	10.92368	0.4002291***	0.0628615
PM	3.465741	4.832949	− 0.3201537	0.4815649	3.076508*	11.81469	0.1684445***	0.0680484
FO	6.689978**	2.53958	− 0.3028073	0.2530788	− 11.81617***	6.212138	0.1707864***	0.0357557
GCV	− 0.1381177**	0.0610387	0.0037063	0.0060429	− 0.866972**	0.1496736	0.0003227	0.0008525
Log SFC	155.0087**	70.93486	− 20.67**	7.015657	441.1471	`173.2596	− 1.292923	0.9914406
Log likelihood	− 451.53836		− 303.07631		− 510.66904		− 175.92108	
Prob > chi^2	0.0005		0.0418		0.0000		0.0000	

*, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Table 12
Tobit regression parameters of input slacks against supply-side variables.

	Cap Slack		PLF Slack		CC Slack		APC Slack	
	Coefficient	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**
LSD	6.799858	4.278823	0.4283231	0.4276611	26.14618**	12.62101	0.3611121***	0.0569284
PM	3.932725	5.167258	− 0.4476555	0.5167828	2.467186	15.2662	0.1606894***	0.0687663
FO	4.664804*	2.285284	− 0.2368356	0.2586012	− 24.7186***	7.64213	0.1762084***	0.0344125
Log likelihood	− 457.06336		− 307.62499		− 528.51257		− 176.93452	
Prob > chi^2	0.0107		0.4874		0.0172		0.0000	

*, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Table 13
Tobit regression parameters of input slacks against demand-side variables.

	Cap Slack		PLF Slack		CC Slack		APC Slack	
	Coefficient	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**	**Coefficient**	**Std. error**
GCV	− 0.0614263	0.0602466	0.0022959	0.0058445	− 0.961903***	0.1419291	0.0031655**	0.0012904
Log SFC	222.9506***	65.17899	− 14.40969**	6.304053	443.6368**	152.611	3.792109**	1.394699
Log likelihood	− 456.44491		− 306.22572		− 512.6111		− 208.11141	
Prob > chi^2	0.0020		0.0731		0.0000		0.0032	

*, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Table 14
Comparison of efficiency scores.

	Base model	Adjusted with supply-side variables	Adjusted with demand-side variables	Both sides adjusted
Mean score	0.764373	0.679035	0.635784	0.64175
H-Statistic		6.345	10.907	10.85

coefficient (0.0863) between the coal quality and the secondary fuel consumption (refer to Table 9) does not support this claim. On the other hand, a reasonable correlation coefficient between low system demand and the log (SFC) imply that the secondary fuel consumption is largely a function of low system demand. Excessive variation in system load or low system demand is exogenously determined by the consumer behaviour, therefore, in this background, normalisation against secondary fuel consumption seems rational. It may be noted that the normalisation function, in this case, is log-linear with respect to the heat rate. The log-linear variation of secondary fuel consumption implies that at a higher rate of consumption the effect on heat rate diminishes. Since the marginal benefit on normalisation diminishes as the secondary fuel consumption goes up, it is likely that the plants would prefer to keep their consumption as low as possible.

Finally, the results obtained from this analysis imply that the coal quality is a key variable that influences the heat rate of power plants. Under the PAT-normalisation framework, the heat rate is proposed to be normalised against the coal quality, possibly under the presumption under the PAT scheme that, controlling the coal quality is beyond the managerial control of the power plant. This assumption, however, goes contrary to the clean-coal initiative of Government of India, which mandates that coal must be cleaned to meet certain quality criteria before its use in the thermal power plant [11,23,32].

This explicitly means that coal quality is controllable, and therefore, normalising the heat rate against the coal quality not only dampens the implementation of clean coal initiative but also rewards the managerial inefficiency by assigning additional heat rate reduction on the basis of poor quality coal through PAT normalisation. This, therefore, may prove to be counter-productive to the objective of the clean-coal initiative as well as the PAT scheme objective. On the other hand, we presume that eliminating the *coal-quality* from the normalisation criteria may prompt the power plants to use clean coal as one of the options for efficiency improvement rather than seeking normalisation for poor quality coal.

7. Conclusions

Normalisation of heat rate on account of operating conditions of a plant is one of the key aspects of monitoring and verification (M & V) of efficiency realisation within the PAT scheme framework. Therefore, for a sound basis for normalising the efficiency, it is essential to establish a credible M & V program. In the PAT scheme, the normalisation criteria have largely been derived from field experiences and empirical studies [5]. In this study, we have attempted to assess the impact of operating conditions on the specific energy consumption of thermal power plants by analysing the cross-sectional variation in operating conditions used for normalisation.

We have examined whether the variability in normalisation variable for coal-based thermal power sector results in a significant difference in heat rate. The normalisation variables are then partitioned into supply-side variables and demand-side variables to separately examine the effect of these variables. A four-stage DEA involving Data Envelopment process followed by Tobit regression is employed to examine the effect of normalisation variables on the efficiency scores.

The study shows that the variability in operating conditions have a significant impact on power plant efficiency, and therefore supports the argument in favour of normalisation as proposed in BEE [5]. However, our study also examines the relative contribution of each variable and suggests some modification that can minimise the need for normalising the heat rate.

The results of our study suggest that out of six normalisation variables as per the PAT normalisation criteria, fuel supply reliability does not have a significant effect on the power plant efficiency. The redundancy of fuel supply reliability implies that either there is a stable fuel supply system to feed the power sector or loss of efficiency due to a fuel shortage gets reflected in other normalisation variables such as forced outage or partial plant unavailability. Therefore, normalising on the basis of fuel supply reliability may lead to assigning double benefits to a plant.

The study also indicates that maximum distortion in efficiency score takes place on account of two demand-side normalisation variables—coal quality and fuel mix effect. However, in view of the clean-coal policy of India, which mandates the use of clean coal for the greater environmental benefit [23], the assumption under the PAT normalisation criteria that coal quality is beyond the managerial control of the power plant seem to be misplaced. Our study suggests that excluding these variables from the PAT normalisation criteria may result in substantial simplification of M & V process of the PAT scheme, without compromising the objective of normalisation. Therefore, instead of normalising the heat rate against coal quality variation, improvement in coal quality by leveraging the clean-coal initiatives of the Government of India may result in furthering the objective of both the PAT policy and clean-coal policy of India.

In case these two variables are excluded from the list of normalisation variables, the need for normalising the efficiency score remains limited to the variability of three supply-side variables—partial unavailability due to low system demand, shutting down of the plant for maintenance, and forced outage. However, the supply-side variables do not impact the efficiency score significantly at 1% level indicating thereby that normalising the heat rate against these three variables is likely to reduce the uncertainties in energy efficiency realisation to a great extent.

The present study, however, assumes the normalisation variables as independent variables and examined its effect on the heat rate. However, in reality, it may be possible that these variables are functions of several underlying factors, such as climatic conditions, and age of the infrastructures etc. Therefore, determining the relationship between the normalisation variables and the underlying factors that explain them may be helpful in providing greater insight into this problem, and possibly come out with further solutions to minimise the uncertainties arising out of normalisation.

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Appendix A

List of the power plants ownership and capacity considered for the study

No.	Power plants	Ownership	Capacity (MW)
1	AMAR KANTAK	State	450
2	ANPARA	State	1630
3	BADARPUR	Central	705
4	BAKRESWAR	State	1050
5	BANDEL	State	450
6	BARAUNI	State	310
7	BHUSAWAL	State	1420
8	BOKARO B	Central	630
9	BUDGE BUDGE	Private	750
10	CHANDRAPUR_MAH	State	2340
11	CHANDRAPURA	Central	750
12	D.P.L.	State	690
13	DADRI (NCTPP)	Central	1820
14	DHANU	Private	500
15	DURGAPUR	Central	340
16	ENNORE	State	450
17	FARAKKA STPS	Central	1600
18	GANDHI NAGAR	State	870
19	GHTP (LEH.MOH.)	State	920
20	GNDTP(BHATINDA)	State	440
21	HARDUAGANJ B	State	470
22	I.B.VALLEY	State	420
23	KOTHAGUDEM	State	720
24	KOTHAGUDEM NEW	State	500
25	K_KHEDA II	State	1340
26	KAHALGAON	Central	1840
27	KOLAGHAT	State	1260
28	KORADI	State	1040
29	KORBA STPS	Central	2600
30	KORBA-EAST	State	940
31	KORBA-WEST	State	840
32	KOTA	State	1240
33	MEJIA	Central	1340
34	METTUR	State	840
35	NASIK	State	910
36	NEWCOSSIPORE	Private	160
37	OBRA-A	State	1322

38	PANIPAT	State	1368
39	PANKI	State	210
40	PARAS	State	500
41	PARICHA	State	640
42	PARLI	State	1170
43	PATRATU	State	770
44	R_GUNDEM - B	Central	63
45	R_GUNDEM STPS	Central	2600
46	RAICHUR	State	1470
47	RAJGHAT	State	135
48	RAYAL SEEMA	State	840
49	RIHAND	Central	2000
50	ROPAR	State	1260
51	SANTALDIH	State	730
52	SATPURA	State	1143
53	SIKKA REP.	State	240
54	SIMHADRI	Central	2000
55	SINGRAULI STPS	Central	2000
56	SOUTHERN REPL.	Private	135
57	SURATGARH	State	1500
58	TALCHER	Central	460
59	TALCHER STPS	Central	3000
60	TANDA	Central	440
61	TENUGHAT	State	420
62	TITAGARH	Private	240
63	TROMBAY_Coal	Private	1400
64	TUTICORIN	State	1050
65	UKAI_Coal	State	850
66	UNCHAHAR	Central	1050
67	VIJAYWADA	State	1260
68	VINDH_CHAL STPS	Central	3260
69	WANAKBORI	State	1470

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